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EXPERT SYSTEM APPLICATION IN MODELLING AND CONTROLLING THE COPPER FLASH SMELTING PROCESS

JOLANTA TALAR, PIOTR JAROSZ, JAN KUSIAK

Akademia Górniczo-Hutnicza, al. Mickiewicza 30, 30-059 Kraków
Corresponding Author: jolanta@talar.pl (J. Talar)

Abstract

The main goal of the paper is an attempt to develop a rule-based expert system (ES) allowing prediction of the key output parameters of a flash smelting process. The expert system knowledge base was built with classification trees (C4.5 algorithm). The second task of the present study was to develop an expert system to support the selection of the control parameters for flash smelting process optimisation. The present paper also describes the results of flash smelting process modelling by using the ES and the concept of ES operation, in turn supporting the process control.

Key words: modelling of metallurgical processes, control system, expert systems, decision trees

1. INTRODUCTION

The work that has been conducted thus far in the field of flash smelting process modelling by using artificial intelligence techniques has comprised the application of artificial neural networks (Talar et al., 2005b; Jarosz et al., 2006; Talar et al., 2006), dynamic neural networks (Stanisławczyk et al., 2006), Bayesian networks (Śledzińska et al., 2005) and regression trees (Talar et al., 2007). The preliminary work in the field of expert system application for flash smelting process modelling possibilities' analysis was also carried out. The paper (Jarosz et al., 2007) describes the results of the prediction of one process output parameter – NO_x concentration in gases, by using an expert system. An attempt to develop a rule-based expert system allowing for the prediction of key output parameters of the copper flash smelting process (condensed phases – copper and slag as well as the gaseous phase of the process) and to evaluate its effectiveness in flash smelting process modelling and controlling were carried out in this study. Algorithm C4.5 of the decision tree induction, based on the data collected under the industrial conditions of one of the smelters, was used to develop a rule-based knowledge base of the expert system. Another task of the present study was to develop an expert system supporting the selection of the control parameters for flash smelting process optimisation. The expert system that was developed is consistent with the concept of flash smelting process controlling based on the model of an artificial neural network as well as process optimisation (Talar et al., 2004; Talar et al., 2005a), in which is a supplement to the developed control system in the field of furnace operators support in selecting the control parameters.

2. EXPERT SYSTEMS

Expert systems (ES) (Hopgood, 2000; Mulawka, 1996) are one of the artificial intelligence branches. Based on detailed knowledge, an expert system can draw conclusions and take decisions, acting in a way

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that is similar to human reasoning. One of most frequently used knowledge notations comprises the rules: 'if a *premise* then *conclusion*'. One of expert systems' basic features is the separation of knowledge encoded in them from the inference system. Moreover, expert systems provide for the possibility to give explanations and to justify the decisions generated. A typical expert system consists of the following main modules: knowledge base, inference engine and explanation subsystem. Figure 1 shows a diagram of an expert system's example construction.

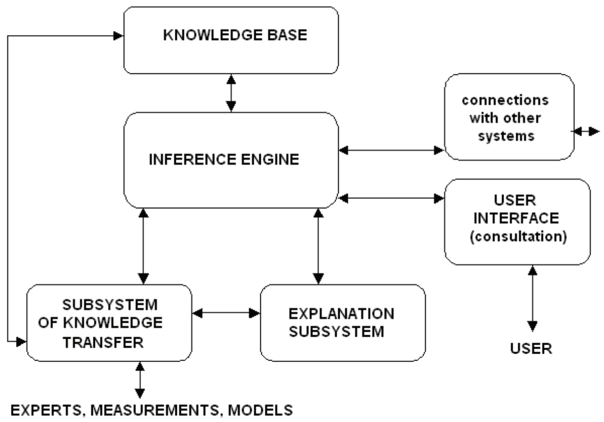


Fig. 1. *Diagram of an expert system's example construction*

Expert systems' effectiveness primarily depends on the quality of the knowledge encoded in the system, in which this knowledge may originate from measurements, analysed process model, information acquired from an expert in specific field, questionnaires, etc.

In addition, algorithms allowing the automation of this arduous process are used to acquire the respective knowledge. These are learning algorithms (Cichosz, 2000), e.g. Bayesian classification, rules, decision trees, Quinlan's algorithm, inter alia.

Quinlan's C4.5 algorithm (Quinlan, 1986; 1993) is a decision tree's induction algorithm and thereby belongs to the data classification techniques. This method allows for presenting knowledge in a simple and clear form, which is easy to understand by humans. The decision tree induction is aimed at finding a set of logical rules, which then may be encoded in an expert system's knowledge base. The diagram of a decision tree's example is shown in figure 2.

In a classification task, a specific object is characterised by the attributes A_i and decision class D_i, to which it belongs. The attributes are those object's features that occur in the test nodes of a decision tree structure (figure 2). Going deeper, starting from the tree root, tests are performed in consecutive nodes, where the specific object's attribute values are checked and depending on the answers obtained in the node, the next test node in the tree will be selected, etc. up to the tree leaf, i.e. for obtaining the answer as to the object's respective proper class. Moreover, the branches in the tree correspond to the results of the tests in the node. In the diagram shown in figure 2 an example of a binary tree is shown, for which the branches correspond to the attribute values 'Y-yes' or 'N-no' that were obtained in the nodes. An example of a rule created based on the decision tree has the following form: *If A1* = 'N' *and A2* = 'Y' *and A3* = 'N' *then D* = 'D3'.

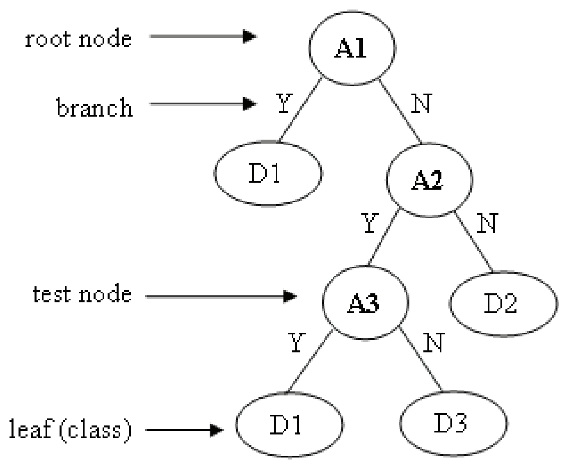


Fig. 2. *Diagram of decision tree construction*

To build a decision tree, a criterion of information increment is used in algorithm C4.5. For the best differentiation between the training examples, heuristics is used in turn resulting in the selection of the feature, which will reduce the estimated information *entropy* to the maximum extent (Talar, 2003). The information contained in the set of training examples is described by equation (1):

$$I(P) = -\sum_{i=1}^{|P|} \frac{|P_i|}{|P|} \log_2\left(\frac{|P_i|}{|P|}\right) \tag{1}$$

where:
P – set of training examples, $P \neq \varnothing$,
$|P|$ – number of examples in training set P,
$|P_i|$ – number of examples describing the i-th object.

The information for attribute a is expressed by equation (2):

$$I(P,a) = \sum_{m=1}^{|V_a|} \frac{|P^{(m)}|}{|P|} I\left(P^{(m)}\right) \tag{2}$$

where:
$\left|P^{(m)}\right|$ – number of examples of values m for attribute a, $P^{(m)} \neq \emptyset$,
$\left|V_a\right|$ – number of values for attribute a.

The criterion for the attribute selection for tree expansion consists of information increment $\Delta I(P,a)$:

$$\Delta I(P,a) = I(P) - I(P,a) \tag{3}$$

Step 1: $I(P)$ value is calculated for the set of examples.
Step 2: $\Delta I(P,a)$ value is calculated for each attribute.
Step 3: attribute a of the maximum information increment $\Delta I(P,a)$ is selected.
Step 4: a node of the tree is created for the selected attribute a.
Step 5: the set of examples P is divided into subsets $P^{(1)}$,...., $P^{(m)}$ corresponding to the values of the test results.
This algorithm is recursively applied to subsets $P^{(1)}$,...., $P^{(m)}$.

The closer the specific attribute (node) is to the root in the created decision tree, the greater its importance in the object's assignment to a specific class (the attribute closer to the root carries more information, acc. to the criterion of the attribute selection for tree expansion).

In addition, during the creation of the decision tree based on examples, Ockham's razor is used to avoid overfitting to the training data (Cichosz, 2000), which 'trims' certain tree fragments in turn replacing them with a leaf (class). This operation increases the error that is obtained in the training file, while reducing the developed classifier testing error and hence results in the generalisation of the knowledge and the possibility of the correct classification of new cases from outside the training set.

The generated decision rules can then be encoded in the expert system's knowledge base, which substantially optimises the space of the expert system searches. In the analysed case (figure 2), the ES will first ask about the value of attribute *A1* and after receiving the user's 'yes' response for this attribute, it stops the inference and gives the solution, while having received a 'no' response, it will ask about the values of subsequent attributes, acc. to their order of occurrence in the tree. In other words, the expert system asks only about selected attributes, which are crucial for the classification and then generates an appropriate decision.

3. FLASH SMELTING PROCESS MODELLING USING RULE-BASED EXPERT SYSTEMS

An attempt was made in the present study to develop a flash smelting process model by using a rule-based expert system allowing for the prediction of key output parameters of the process. The expert system's knowledge base was established based on those rules generated with the use of decision trees algorithm C4.5 based on industrial measurements data.

The data from the period 1 August 2005 to 5 June 2006 was used to develop a flash smelting process model. The data sets were filtered with regard to the permissible process parameters limits as specified by process engineers. In addition, the parameters of the process gaseous phase were additionally filtered by using the adaptive filters method (Stanisławczyk et al., 2007) that is based on dynamic neural networks. The adaptive filtration was aimed at the elimination of those measurement records for which the output parameters of the gaseous phase were disturbed by those operations not registered in the database (e.g. furnace inspection, sensors test and others). As a result, the measurement data used in the analysis comprised 6,987 records for the process condensed phases (5,271 training records and 1,746 test records) and 6,836 records for the gaseous phase (5,127 training records and 1,709 test records).

3.1. Flash smelting process parameters

20 input parameters and 9 output parameters of the flash smelting process were selected for analysing, which are shown in tables 1 and 2, respectively. In previous studies in the field of flash smelting process modelling, a set of 27 input parameters was used (Talar et al., 2006). In the present study the total feed of the concentrate and total feed of the IOS product (without breaking down into individual burners) were used, which in turn reduced the number of input parameters, while no significant parameter analysed so far has been eliminated.

Table 1. *Analysed process input parameters and training data ranges*

Process input parameters		unit	min	max
WE1	total concentrate feed	Mg/h	80	112.51
WE2	backward dusts	Mg/h	0	16.28
WE3	total IOS feed	Mg/h	0	7.16
WE4	oil into the reaction shaft	l/h	76	1103
WE5	O_2 concentration in the blow	%	73.81	82.63
WE6	hyper-oxidation	Nm^3/Mg	222	286
WE7	aeration on burner 1	Nm^3/h	159	240
WE8	aeration on burner 2	Nm^3/h	160	240
WE9	aeration on burner 3	Nm^3/h	160	240
WE10	aeration on burner 4	Nm^3/h	0	260
WE11	aeration on dust burner	Nm^3/h	130	250
WE12	C_{org} content in the concentrate	%	5.69	7.43
WE13	Cu content in the concentrate	%	25.3	31.24
WE14	S content in the concentrate	%	9.56	14.8
WE15	Pb content in the concentrate	%	0.88	1.61
WE16	SiO_2 content in the concentrate	%	16.14	21.82
WE17	CaO content in the concentrate	%	4.87	6.99
WE18	H_2O content in the concentrate	%	0.15	0.36
WE19	fraction of sub-grains in the concentrate	%	2.3	60.6
WE20	fraction of super-grains in the concentrate	%	0	1.7

Table 2. *Analysed process output parameters*

Process output parameters	unit
Cu concentration in slag	%
Fe concentration in slag	%
Pb concentration in slag	%
SiO_2 concentration in slag	%
CaO concentration in slag	%
Pb concentration in blister Cu	%
SO_2 concentration in gases	%
CO_2 concentration in gases	%
NO_x concentration in gases	ppm

The problem in flash smelting process output parameter prediction was reduced to the classification issue. The values of the process output parameters were divided into decision classes acc. to the criteria specified by process engineers (table 3, table 4).

For each of the process output parameters analysed, a knowledge base was prepared, allowing for the prediction of a specific parameter's level: 'low', 'medium', and 'high'.

Table 3. *Decision classes for slag and blister copper parameters*

Process output parameter	Decision classes: three levels of output parameters		
	low	medium	high
Cu concentration in slag	(…;12)	<12;14)	<14;…)
Fe concentration in slag	(…;6)	<6;9)	<9;…)
Pb concentration in slag	(…;2>	(2;2.5>	(2.5;…)
SiO_2 concentration in slag	(…;33)	<33;34)	<34;…)
CaO concentration in slag	(…;13.7)	<13.7;14>	(14;…)
Pb concentration in blister Cu	(…;0.18)	<0.18;0.22>	(0.22;…)

Figure 3 shows a fragment of a developed decision tree structure related to the analysis of the Pb concentration in the blister copper.

A thick line (figure 3) denotes the way the rule creation was based on the decision tree: *If* we6<=253 *and* we4>97 *and* we15<=1.22 *and* we4>100 *and* we15<=1.16 *then* Pb_in_blister_Cu= 'low'. After simplification, the rule will have the following shape: *If* we6<=253 *and* we4>97 *and* we15<=1.16 *and* we4>100, *then* Pb_in_blister_Cu= 'low'. Based on the analysed tree (figure 3), a set of 376 decision rules was created, which were subsequently encoded in the expert system's knowledge base.

Rules allowing for the prediction of nine analysed process output parameters were created in the way as described above. The expert system by using the developed decision rules applies a 'backward' searching strategy in order to determine the values of the analysed process output parameters.

Table 4. *Decision classes for process gaseous phase parameters*

Process output parameter	Decision classes: four levels of output parameter			
	low	medium	high	very high
SO_2 concentration in gases	(…;19)	<19;21)	<21;23)	<23;…)
CO_2 concentration in gases	(…;35)	<35;40)	<40;45)	<45;…)
NO_x concentration in gases	(…;800)	<800;1000)	<1000;1200)	<1200;…)

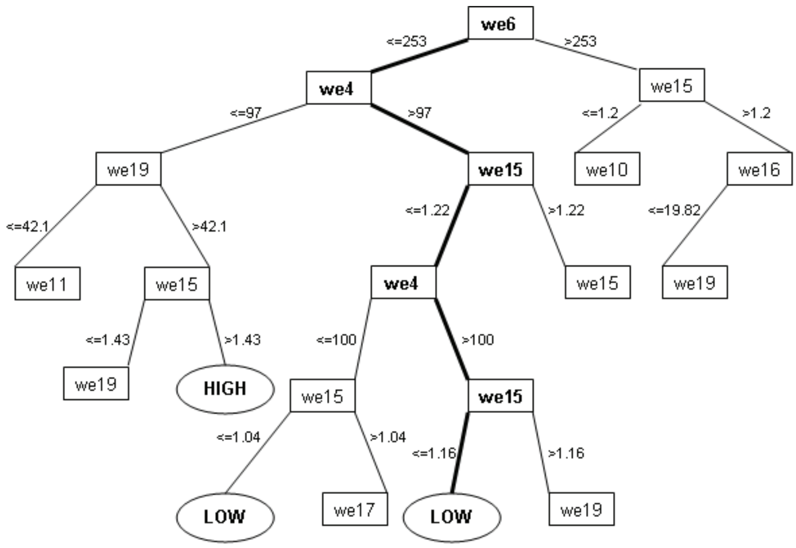


***Fig. 3.** Fragment of a decision tree created to predict the level of the Pb concentration in the blister copper.*

The best results were obtained when predicting the level of Fe and Pb content in slag. The percentage of the correct ES answers for these parameters was more than 90%. However, in the case of process gaseous phase parameter modelling, the best results were obtained when predicting the NO_x and CO_2 content in gases, for which the percentage of the correct results was between 87% and 89%.

From the process point of view, the prediction results are satisfactory and acceptable for the SiO_2 and CaO content in slag and Pb in blister copper, as well as the SO_2 concentration in gases, for which the results' correctness ranged between 83% and 85%.

Unfortunately in some cases, despite the fact that the percentage of the correct ES answers was pretty high (from 83% to 86%), certain ranges of those parameter values were predicted with rather poor accuracy of approx. 60%. In the case of predicting 'low' CaO concentration in slag, a 95% result accuracy was achieved, while the other levels - 'medium' and 'high' - were predicted with an accuracy of 64-68%. A similar situation occurred in predicting the Cu concentration in slag, where two levels of this parameter – 'medium' and 'high' – were predicted with a high precision of 88-92%, while one class – 'low' level of Cu in slag – was predicted with an accuracy of 54%. Models for the analysed process output parameters were developed based on the data from the same period of flash smelting furnace operation. However, a relatively small number of records described a 'low' level of Cu concentration in slag (only 13% of the training records described this class) and the 'medium' and 'high' levels of CaO in slag (each of these classes had only 14% examples in the training set), which may explain the rather poor quality of these categories' prediction. In addition, it is necessary to mention here the process conditions, which were related to the classes of these parameters as discussed above:

3.2. Results of the flash smelting process modelling

The developed process models were tested on industrial data. To evaluate their quality, the percentage of the correct expert system's answers was calculated for the test set comprising approx. 1,700 records. The results of the slag and blister copper parameters modelling are shown in table 5, while the results of process gaseous phase parameters modelling are shown in table 6.

***Table 5.** Results of the slag and blister copper parameter prediction by the ES*

Process output parameter	Total % of the correct answers	% of the correct answers for the individual levels of the output parameter		
		low	medium	high
Cu concentration in slag	**85%**	**54%**	**88%**	**92%**
Number of correct answers	1492	116	838	538
Number of test records	1746	215	947	584
Fe concentration in slag	**93%**	**93%**	**92%**	**94%**
Number of correct answers	1620	439	563	618
Number of test records	1746	474	613	659
Pb concentration in slag	**91%**	**89%**	**94%**	**90%**
Number of correct answers	1597	589	867	141
Number of test records	1746	662	927	157
SiO_2 concentration in slag	**83%**	**88%**	**79%**	**75%**
Number of correct answers	1441	691	586	164
Number of test records	1746	789	738	219
CaO concentration in slag	**86%**	**95%**	**68%**	**64%**
Number of correct answers	1497	1129	167	201
Number of test records	1746	1187	247	312
Pb concentration in blister Cu	**85%**	**90%**	**76%**	**83%**
Number of correct answers	1479	836	408	235
Number of test records	1746	924	538	284

__Table 6.__ Results of the process gaseous phase parameter prediction by the ES

Process output parameter	Total % of the correct answers	% of the correct answers for the individual levels of the output parameter			
		low	medium	high	very high
SO_2 concentration in gases	**85%**	**86%**	**86%**	**87%**	**61%**
Number of correct answers	1452	195	674	528	55
Number of test records	1709	227	787	605	90
CO_2 concentration in gases	**87%**	**89%**	**89%**	**86%**	**84%**
Number of correct answers	1485	232	416	638	199
Number of test records	1709	262	466	743	238
NO_x concentration in gases	**89%**	**82%**	**92%**	**85%**	**94%**
Number of correct answers	1526	103	821	450	152
Number of test records	1709	126	895	527	161

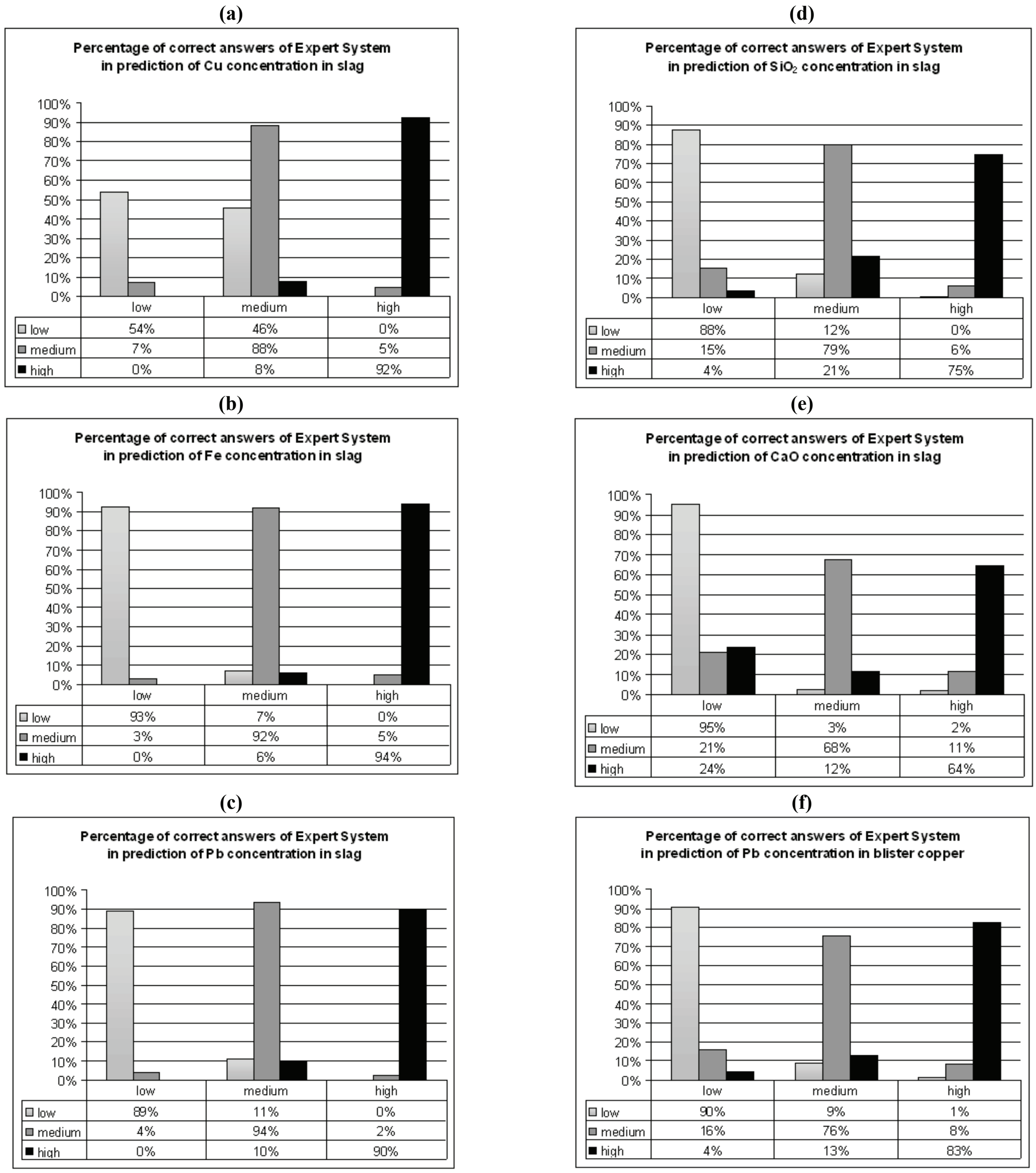


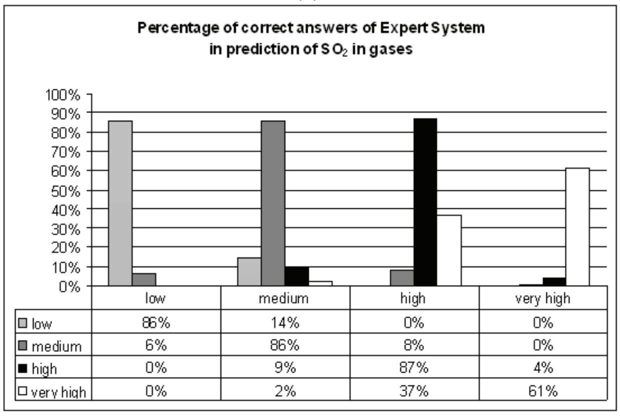
__Fig. 4.__ Results of the expert system application in predicting the slag and blister copper parameters.

- low level of Cu concentration in slag is not a problem for the process unless the level of lead concentration in the copper is exceeded,
- also medium and high levels of the CaO concentration in slag is not a significant process problem, because usually that implies substantial savings at the stage of copper removal.

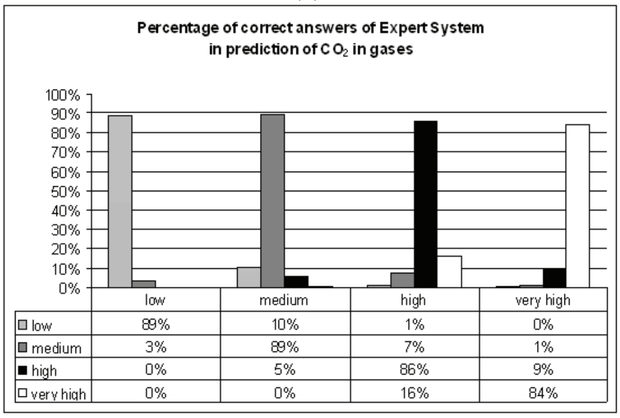
On the one hand, such a situation generates a relatively small number of measurement records in those ranges, and on the other hand – a possibility of the occurrence of additional, hardly noticeable 'noises' in the measurement records used.

The graphical interpretation of the results obtained by the expert system is shown in figures 4 and 5.

(a)



(b)



(c)

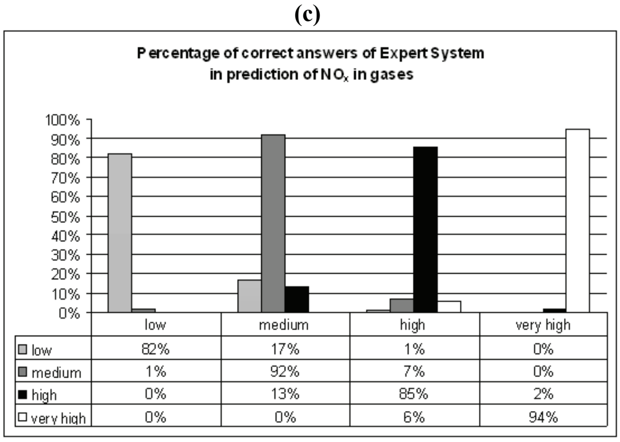


***Fig. 5.** Results of the expert system application in predicting the flash smelting process gaseous phase parameters.*

As it can be seen in figures 4 (b-c) all the levels of the Fe and Pb content in slag were predicted by the expert system with a very high precision of ca. 90%. The results of Pb in blister copper (figure 4 (f)) and of SiO_2 in slag (figure 4 (d)) prediction were also on an acceptable level. However, figures 4 (a) and 4 (e) show the results of the prediction of the Cu levels in slag and of CaO in slag, for which not all the ranges of those parameters were predicted with sufficient accuracy.

Figure 5 shows the results of the process gaseous phase parameter prediction. The best results' quality was obtained in predicting the NO_x and CO_2 concentration in gases (figures 5 (c) and 5 (b)), where all the levels of those parameters were predicted with a high accuracy of approx. 90%. Figure 5 (a) shows the results of the SO_2 concentration in gas prediction, where one of the categories was predicted with an accuracy of approx. 60%, while the other classes with an accuracy exceeding 80%. It can safely be assumed that the reduction of the decision class number to three levels of gaseous phase parameters can contribute to an improvement in the expert system results.

3.3. Examples of decision rules

The developed expert system operates in programme mode, i.e. collects the input data from the database, activates the inference module, generates the decision based on the knowledge encoded in the knowledge base and records the results obtained in an external database. In the inference process, the ES uses the rules contained in the knowledge base and applies a 'backward' searching strategy.

There is also a possibility to work with the expert system in a conversational mode. In this case, the user provides answers to questions and the explanation module provides the justification of the decision made by quoting the rules used in the inference process. Figure 6 shows the applied rules and facts in predicting the level of Pb in blister copper for two examples of the test data records: (a) – in the case of a 'high' Pb level in copper and (b) – for a 'low' Pb level in blister copper.

As it results from figure 6, important facts affecting the prediction of a 'high' Pb level in blister copper include: *we6* – hyper-oxidation, *we15* – Pb content in the concentrate, *we16* – SiO_2 content in the concentrate, *we19* – fraction of sub-grains in the concentrate, *we5* – O_2 concentration in the blow, *we18* – H_2O content in the concentrate, *we1* – total concentrate feed, *we17* – CaO content in the concentrate; while for the prediction of a 'low' Pb level in blister copper, the important facts are: *we6* – hyper-oxidation, *we4* – oil into the reaction shaft, *we15* – Pb content in the concentrate.

(a)

pb_blister = "HIGH"

KONKLUZJA: pb_blister = "HIGH"
14: pb_blister = "HIGH" **JEŚLI**
we6 > 253.00 **i**
we15 > 1.20 **i**
we16 <= 19.82 **i**
we19 > 45.10 **i**
we5 > 79.11 **i**
we18 > 0.26 **i**
we1 <= 103.60 **i**
we16 <= 19.13 **i**
we17 > 5.67 **i**
we17 > 5.78;

6* Fakt :we6 = 257.00
15* Fakt :we15 = 1.54
16* Fakt :we16 = 18.27
19* Fakt :we19 = 47.20
5* Fakt :we5 = 81.27
18* Fakt :we18 = 0.30
1* Fakt :we1 = 89.90
17* Fakt :we17 = 5.99

(b)

pb_blister = "LOW"

KONKLUZJA: pb_blister = "LOW"
1: pb_blister = "LOW" **JEŚLI**
we6 <= 253.00 **i**
we4 > 97.00 **i**
we15 <= 1.22 **i**
we4 > 100.00 **i**
we15 <= 1.16;

6* Fakt :we6 = 240.00
4* Fakt :we4 = 199.00
15* Fakt :we15 = 1.16

Fig. 6. *Examples of decision rules that are used in the ES inference process (a) – for a 'high' Pb level in blister copper and (b) – for a 'low' Pb level in blister copper.*

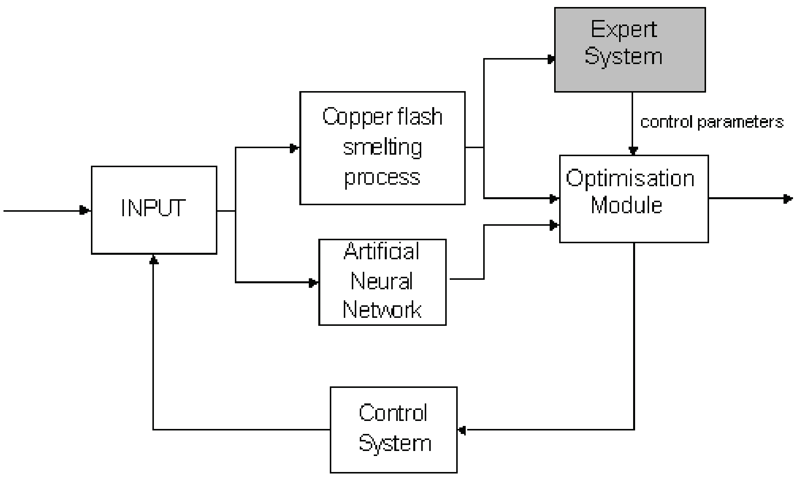


Fig. 7. *Expert system location in the flash smelting process control system.*

The lead content in the blister copper obviously depends on its stream in the furnace feed. The relationships found show that fact via a combination of the *we15* and *we1* parameters. From a technological point of view, the dependence on other concentrate components' concentration is also visible and understandable, i.e. on silica – *we16* and calcium oxide – *we17* as well as on the size composition of the concentrate fed – *we19*. This is related to reaction thermodynamics in a furnace reaction shaft and to the possibilities of e.g. lead silicates formation.

The conclusion related to the priority role of hyper-oxidation (*we6*) for the analysed parameter value is also very important. Industrial practice shows that if there is too high of a Pb concentration in blister copper, then the value of hyper-oxidation (*we6*) should be increased to reduce the level of Pb concentration in copper. From the relationships shown by the ES (figure 6) it results that the occurrence of a high Pb concentration in blister copper is accompanied by the occurrence of high hyper-oxidation (above 253 Nm^3/Mg). This may be interpreted as a clear recommendation to use high hyper-oxidation at a high Pb concentration in copper, which will result in this concentration's decrease to the required level. At the same time, a low level of Pb concentration in copper allows for the reduction of hyper-oxidation (hence, the production costs).

4. EXPERT SYSTEM APPLIED TO THE SELECTION OF FLASH SMELTING PROCESS CONTROL PARAMETERS

The expert system that was developed in the present study is aimed at assisting operators in selecting the control parameters to be optimised.

The expert system is one of the components of the flash smelting process control system in preparation. The general concept of a process control system is presented in diagrammatic form in figure 7. A process model that is based on artificial neural networks is used to control the flash smelting process, which based on 27 input parameters predicts the values of 16 output parameters of the process. The optimisation module based on genetic algorithms is activated in the event of output parameters' disturbance. The furnace operator indicates as to which input parameters should be optimised, while the optimisation module determines the optimum values of these parameters to restore the proper course of the process. The ES that is suggested in the present paper could be a tool for operators' decision support in selecting the control parameters to be optimised.

4.1. Analysed process control parameters

Within the present study, a set of 10 input parameters of the process was selected for analysis (table 7), which allows for the controlling of the flash smelting furnace operation in real-time. On the flash smelting process input, there is also a number of other important process parameters, inter alia characterising the concentrate composition. However, because of the long time of waiting for changes in the process' course in turn resulting from the concentrate parameters' change, these parameters cannot be considered control parameters. Therefore, for the needs of this analysis at hand, the set of input parameters was limited to only 10 control parameters.

Table 7. *Analysed process control parameters*

Process input parameters		unit
WE1	total concentrate feed	Mg/h
WE2	backward dusts	Mg/h
WE3	total IOS feed	Mg/h
WE4	O_2 concentration in the blow	%
WE5	hyper-oxidation	Nm^3/Mg
WE6	aeration on burner 1	Nm^3/h
WE7	aeration on burner 2	Nm^3/h
WE8	aeration on burner 3	Nm^3/h
WE9	aeration on burner 4	Nm^3/h
WE10	aeration on dust burner	Nm^3/h

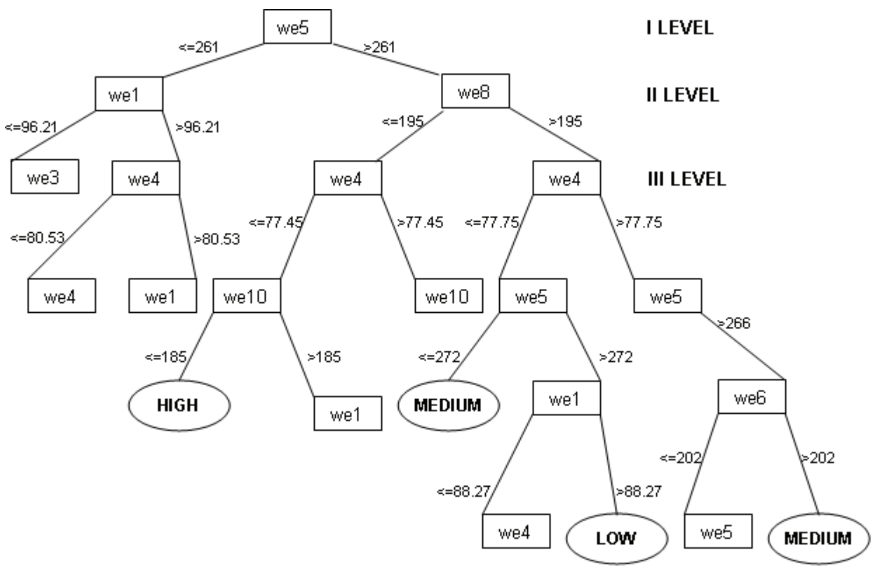


Fig. 8. *Fragment of the decision tree structure to analyse the level of the Pb concentration in slag, which was worked out based on 10 process control input parameters.*

In addition, a set of crucial output parameters of the process was selected for analysis (table 8), which decides about the final products' quality. The compliance with the technological limits of the analysed output parameters is a necessary condition for the proper process course.

Table 8. *Analysed process output parameters*

Process output parameters	unit
Cu concentration in slag	%
Fe concentration in slag	%
Pb concentration in slag	%
SiO_2 concentration in slag	%
CaO concentration in slag	%
Pb concentration in blister Cu	%
SO_2 concentration in gases	%
CO_2 concentration in gases	%
NO_x concentration in gases	ppm

4.2. Decision tree analysis and knowledge acquisition

The decision trees were analysed in order to acquire knowledge for the expert system supporting the selection of the control parameters.

For each of the process output parameters, a decision tree was individually generated using algorithm C4.5. A set of 10 control parameters was used in the analysis (table 7). An example of a decision tree that was created to analyse the Pb concentration in slag is shown in figure 8.

The sequence of attributes' occurrence in the decision tree corresponds to the significance hierarchy of these attributes as assigned to specific class objects. The structures of the developed decision trees were analysed, wherein the control parameters were analysed to the third level in the tree, starting from the tree root. Three levels of the decision trees are shown in figure 8, which were analysed with a view to selecting the control parameters. Each tree was analysed individually, as well as the groups of trees for the technologically determined parameters groups. The collected knowledge was recorded in the form of decision rules in the expert system's knowledge base.

The set of data to construct the decision trees comprised approx. 5,000 records, and the test data set for their verification consisted of approx. 1,700 records. The obtained results from the developed decision tree testing are shown in table 9. Despite the substantial limitation of the number of input parameters analysed, the percentage of the correct results is satisfactory and equal to 70%-80%.

Table 9. *Results of the process output parameter prediction based on the control parameters, by using decision trees.*

Process output parameter	Total % of the correct answers
Cu concentration in slag	77%
Fe concentration in slag	80%
Pb concentration in slag	75%
SiO_2 concentration in slag	70%
CaO concentration in slag	75%
Pb concentration in blister Cu	71%
SO_2 concentration in gases	76%
CO_2 concentration in gases	79%
NO_x concentration in gases	79%

4.3. An example of expert system operation for supporting control parameters selection

The expert system may work in a programme or conversational mode. The conversational mode consists in ES dialogue with the user to acquire facts that are used by the ES during inference. However, in the programme mode the system collects the data from an external database on its own, activates the inference module and generates decisions. In industrial conditions the application of the programme mode is a better solution due to the necessity of process control in real-time. However, the conversational mode is shown in the present paper in order to present expert system capabilities.

In the conversational mode it is necessary to indicate on the ES input as to which process output parameters are disturbed. Then, the ES activates the inference module and generates decisions based on the rules encoded in the knowledge base. The result of an expert system operation consists of information stating as to which parameters should be con-

(a)

(c)

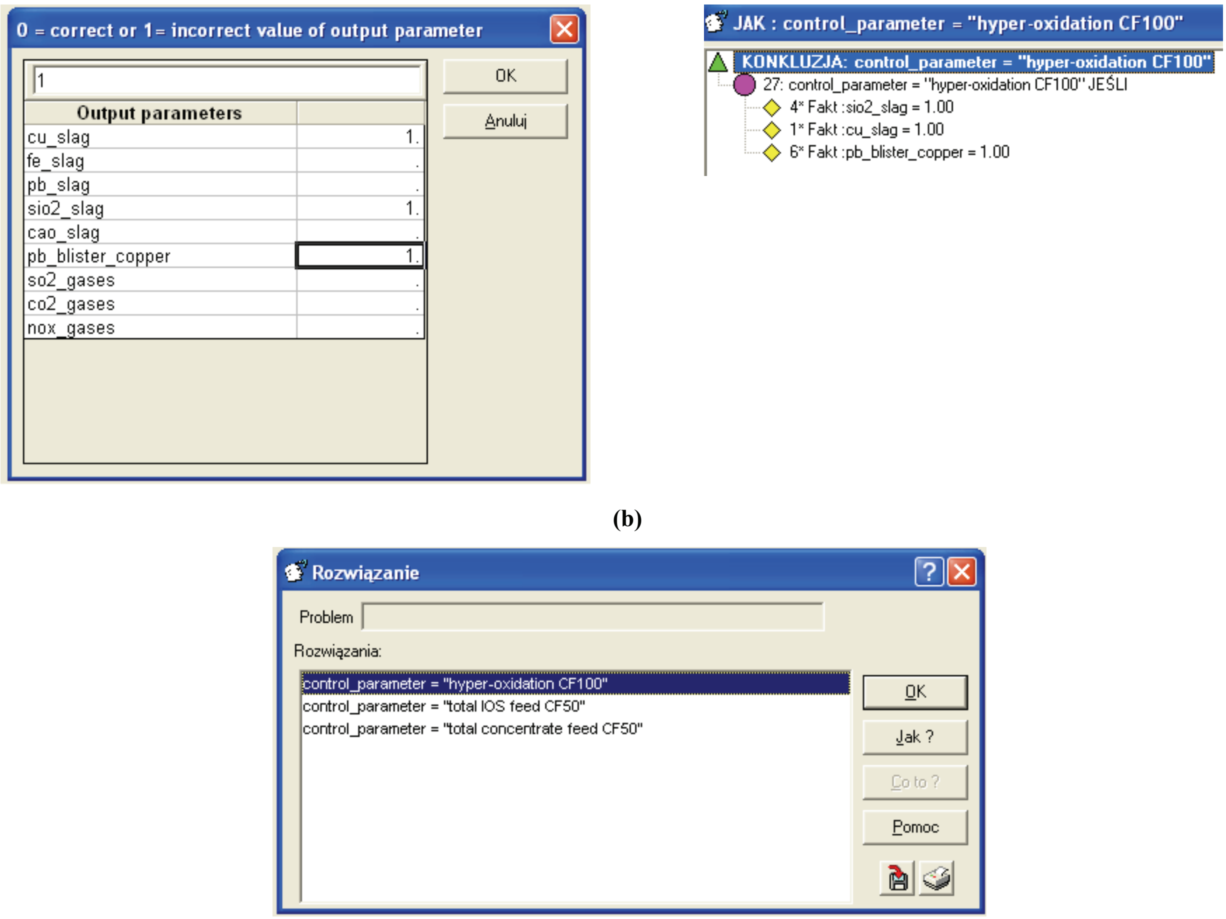


Fig. 9. Example of ES operation in the conversational mode for a few disturbed process output parameters: (a) – dialogue with the user, (b) – window presenting the ES solution, (c) - ES explaining module.

trolled. The system suggests a number of control parameters, wherein for each answer a significance coefficient CF is determined that shows the control significance hierarchy of a specific parameter. The operator may select one or a few control parameters to be optimised. However, the final decision is always to be made by the furnace operator.

An example of ES operation is shown in figures 9-10. The ES can also explain the decision made by quoting the rules and facts that are used in the inference process. Figure 9 shows the ES operation in the case of a number of process output parameters' disturbance, while figure 10 shows the ES operation in the case of single output parameter disturbance.

with the appropriate level of the output parameters. This is obviously consistent with the thermodynamic analysis of the process. The hyper-oxidation plays the main role for key parameters (Cu in slag, Pb in copper, gaseous phase composition). It is rather important to find out the role of endothermic agents directed to the process (IOS product, dusts) and their relationship to the concentrate feed. This indicates the need for the strict control of the process energy balance. This is also proven by the influence of e.g. the oxygen concentration in the blow on gaseous phase composition (hence, the oxygen and air interrelationship in the blow). This is a hint for the process operator, how e.g. the increase in hyper-

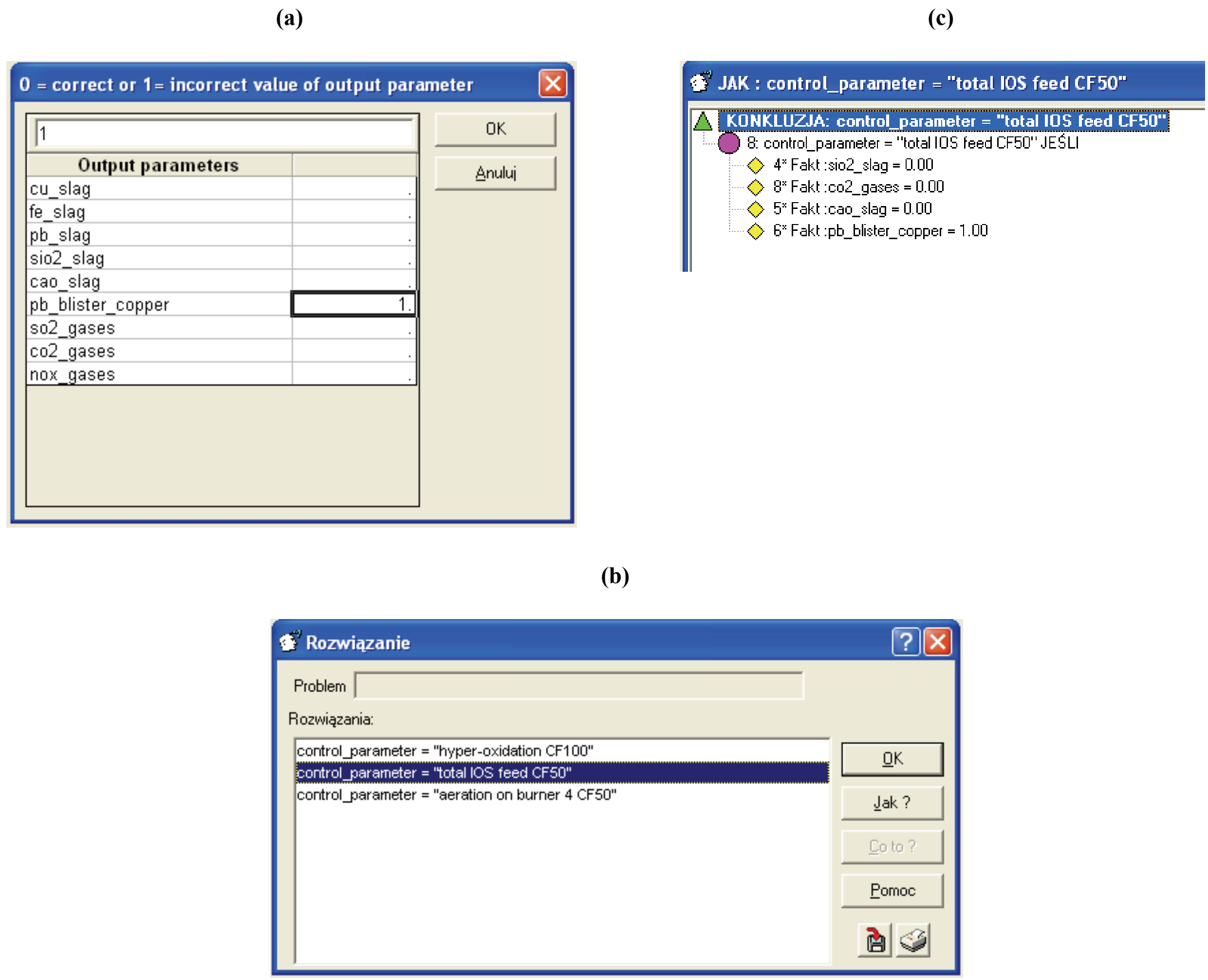


Fig. 10. Example of ES operation in the conversational mode in the case of one disturbed process output parameter: (a) – dialogue with the user, (b) – window presenting the ES solution, (c) – ES explaining module.

4.4. Technological verification of the developed ES knowledge base

From the process point of view, the messages that were generated by the ES clearly indicate the need of an hyper-oxidation adjustment to comply

oxidation is to be implemented. Moreover, when analysing the results that were obtained, it is necessary to remember that they were obtained based on the industrial data analysis. Such data, despite the fact that it *strictly* applies to technological issues, is always (!) burdened with the hidden influence of process economics on the respective technology. Sometimes this creates interpretative problems. To summarise, the obtained results may be considered a technological-economic model for flash smelting process control. The expert system suggests the control parameters, while the operator, taking into account the economic criteria, makes the final decision and selects the appropriate control parameters for process optimisation.

5. SUMMARY

Models allowing for the prediction of the output parameters of flash smelting process by using rule-based expert systems have been developed within the present study. The advantages of the approach applied include the transparency of the knowledge acquired, encoded in the expert system's knowledge base, which is available to the user. This provides the possibility of a broader analysis of the process and of the interrelationships between the process input and output parameters. The developed models have been tested on the industrial data and their operation quality is satisfactory for the majority of the parameters analysed. Despite the fact that the suggested models do not predict continuous values of the process, in a qualitatively correct way they indicate the individual levels of the analysed process output parameters ('low', 'medium' and 'high').

The expert system supporting the process control that was developed in the second part of the present study is worth emphasising. The worked out decision trees were analysed and the parameters' significance hierarchy was determined for flash smelting process control, which in turn allowed for the working out of this expert system's knowledge base.

The knowledge that was acquired in the field of decision support for the control parameters' selection was technologically verified, which has in turn confirmed the correctness of the system operation.

The application of the developed expert system in industrial practice may allow for the use of uniform and universal procedures in the field of process control. It should be emphasised that the knowledge acquired to develop the expert system was acquired from industrial data sets, comprising various control techniques and approaches that are used by various furnace operators.

The results obtained also confirm the effectiveness of the applied research methodology that is based on decision trees and rule-based expert systems in modelling and controlling the flash smelting process of copper manufacturing.

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ZASTOSOWANIE SYSTEMU EKSPERTOWEGO W MODELOWANIU I STEROWANIU ZAWIESINOWYM PROCESEM WYTWARZANIA MIEDZI

Streszczenie

W ramach niniejszej pracy podjęto próbę opracowania regułowego systemu ekspertowego (SE) pozwalającego na przewidywanie kluczowych parametrów wyjściowych procesu zawiesinowego. Baza wiedzy systemu ekspertowego została opracowana na podstawie drzew klasyfikacyjnych (algorytm C4.5). Drugim zadaniem niniejszej pracy było opracowanie systemu ekspertowego wspomagającego wybór parametrów sterujących do optymalizacji procesu zawiesinowego. W pracy przedstawiono wyniki modelowania parametrów procesu zawiesinowego przy wykorzystaniu SE oraz ideę działania SE wspomagającego sterowanie procesem.

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